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Performance Evaluation of Medium-Term Load Forecasting Approaches: A Case Study of Ogun State, Nigeria

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Abstract

The place of electrical energy in enhancement of this computer age cannot be over-emphasised. Its forecast plays a significant functions in energy industry, helps the government and private sectors in making the precise decision regarding energy management practices. This paper presents performance evaluation of medium-term load forecasting techniques: a case study of Ogun State, Nigeria. Two different approaches were used using the previous load consumption in 2017 for the forecast. Least square approach compared with regression exponential approaches gave the least value of Mean Average Percentage Error (MAPE) and Root Mean Square Error (RMSE), which are 1.8212% and 0.004472 respectively. The anticipated percentage load growth for the months of July-December, 2018 forecasted with least square approach were 34.06%, 33.54%, 36.10%, 31.10%, 32.23% and 30.15% respectively, acute gas supply caused by pipeline vandalisation and theft of distribution/sub-station materials could be held responsible for low load growth in the month of December. The results of this analysis will assist the Regional Headquarters, Ibadan Electricity Distribution Company (IBEDC), Abeokuta, Ogun State in making effective planning, operation and management of energy across the state.

Keywords

Least square model;
Load forecast;
MAPE;
Monthly load growth;
Regression exponential model;
RMSE.

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1. Introduction

Electrical energy is ranked as one of the most essential resources needed to pivot developmental activities of any community or country (Okundamiya *et al.,* 2014). The amount of electrical energy available largely dictates the extent of growth that would occur both at industrial and domestic level (Eneje *et al.,* 2012; Minaye & Matewose, 2013; Saab *et al.,* 2000). The demand for this electrical energy is a direct function of weather variables, human social activities, industrial activities as well as community developmental involvement (Cheepati & Prasad, 2016). The exponential growth in demand for power does not commensurate with the growth in supply of power hence; a serious challenge is created by this energy-demand gap for power system engineers in power utilities companies (Amlabu *et al.,* 2013; Volkan & Husevin, 2001). The need for efficient/precise prediction of what energy demand will be on hourly, weekly, monthly or annually basis has to be adequately forestalled and one of such scheme for doing this task is load forecasting.

Load forecasting is a tool for predicting the hourly, daily, weekly, monthly and yearly values of the system load, peak system load and system energy demand (Gross & Galiana, 1987). It encompasses the precise forecast of both the magnitudes and geographical location of electric load over the diverse periods of planning horizon (Amlabu *et al.,* 2013). Accurate load forecasting not only helps users in the choice of more appropriate electricity consumption scheme and reduction of expenditure on electric energy but also a conducive means of optimising power systems resources with a view to improving electric power supply capability and ultimate realization of conservation of energy and emission reduction objectives (Hu *et al.,* 2017; Jianwei *et al.,* 2018; Li *et al.,* 2014).

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Load forecasting enhances efficient planning, operation and management of the electricity industry and electric power systems as a whole. If a precise forecast is made, substantial savings in operation and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development can be achieved (Minaye & Matewose, 2013). It is of immense benefit to electric utility as it provides important guide in making informed decisions as per purchasing and generating electric power, load switching, and infrastructure development (Yuansheng *et al.,* 2016). Based on the length of time involved, load forecasting can be classified as short-term (STLF), medium-term (MTLF), and long-term load forecast (LTLF) (Singh *et al.,* 2012).

Medium- term load forecast (MTLF) is of interest in this paper, it refers to forecast within a time frame of one month to one year (Chandra & Satyanaravana, 2013; Sadowruk & Barbosa, 1999). MTLF finds application in planning of fuel procurement, scheduling unit maintenance, energy training and revenue appraisal. Miscellaneous uses of MTLF entails decisions on capital repairs, inventory control of coal and liquid fuels, the purchase of fuel quantities and the assessment of revenue impacts due to changes in electricity tariffs (Cullen, 1999). Several researchers have proposed and implemented different load forecasting techniques, which can be classified into two major classes; the classical prediction methods and novel prediction method based on artificial intelligence techniques (Brodowski *et al.,* 2017; Germi *et al.,* 2014; Jianwei *et al.,* 2018; Wang *et al.,* 2016). Classical methods among others include regression analysis, time series method, grey prediction method while artificial intelligence techniques includes artificial neural network, genetic algorithm, particle swarm optimization and bacterial foraging optimisation (Ei *et al.,* 2001; Jianwei *et al.,* 2018; Lu & Zhou, 2009; Yang & Li, 2006). Peculiar techniques applicable to MTLF found in literatures so far are trend analysis, end-use models, econometric models statistical model based learning, artificial neutral network and support vector machine (Papaioannou *et al.,* 2016).

This paper presents performance evaluation of medium-term load forecasting approaches: a case study of Ogun State, Nigeria. The rest of this paper is organised as follows: Section 2 presents the materials and method. Section 3, presents the discussion of results while section 4 presents conclusion.

2. Materials and Methods

2.1. Description of Study Area

The study location is Ogun State, Nigeria found between longitude and latitude 6.9075°N, 3.5813°E respectively. Abeokuta serves as the capital of the state which houses the regional office of Ibadan electricity distribution company (IBEDC). The state population as at 2016 census stood at 5,217,700 and total surface area is 16,762km^2 while her population density was estimated to be 311.3/km. IBEDC regional office in Abeokuta controls six business hubs (BHs) namely Ijeun, Olumo, Sagamu, Ijebu-ode, Ota, and Sango, its operating voltage level is 132/33/11/0.415 kV. These transmission stations feed 33 kV feeders and 27 injection substations owned by IBEDC, which inter-supply electricity to 47 number of 11 kV feeders across the entire state. Figure 1 shows the location of six business hubs across the study area.

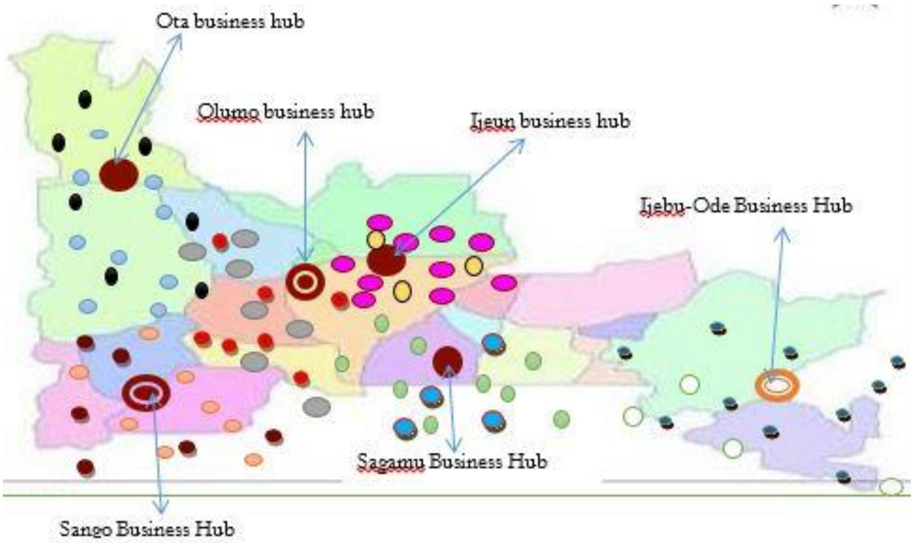

Figure 1. Location of six business hubs across the study area

2.2. Acquisition of Field Data and Implementation Tool

The monthly energy consumption in megawatt hour (MWh) in Ogun State from January 2017 to December, 2017 was collected for the analysis. The monthly energy consumption in megawatt (MW) was derived from the data collected and was used in the analysis. The collected data over a period of 12 months is shown in Table A (Appendix).

A comparative performance evaluation of regression exponential and least square techniques on medium-term load forecasting was done using MAPE and RMSE as performance metric. The MAPE and RMSE are commonly used indicators for comparing error terms of models (Okundamiya & Okpamen, 2013; Okundamiya *et al.,* 2016). Micro-Soft Excel was used for the computational analysis in this research.

2.3. Mathematical Modelling of Techniques Used For the Load Forecasting

2.3.1 *Least Square Approach:* This is one of the effective techniques of obtaining a good fit to a given data. The detailed mathematical derivation of the least square technique is given by Wang *et al.* (2016). Given a straight line in its simplest form as:

$$y = a_0 + a_1 x, \tag{1}$$

where, y is the dependent variable, x is the independent variable a_0 is the intercept on y-axis and a_1 is the gradient of the line.

Applying the least square approach, the values of a_0 and a_1 can be obtained thus:

$$Sum = S = \sum_{i=1}^{n}(e_i^2) \tag{2}$$

$$= \sum[(Observed\ Values) + (Predicted\ values)]^2 \tag{3}$$

$$= \sum_{i=1}^{n}[y_i - (a_0 + a_1 x\ )]^2 \tag{4}$$

Opening up (4) and differentiating the resulting equation with respect to a_0 and a_1 then:

$$na_0 + a_1 \sum x_i = \sum y_i \tag{5}$$

$$a_0 \sum x_i + a_0 \sum x_i^2 = \sum x_i y_i \tag{6}$$

Solving (5) and (6) simultaneously; the values of a_0 and a_1 is obtained thus:

$$a_1 = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x_i^2 - (\sum x_i)^2} \tag{7}$$

$$a_0 = \frac{\sum y_i - a_1 \sum x_i}{n} \tag{8}$$

2.3.2 *Regression Exponential Approach:* The detailed mathematical modelling of this approach is given by Wang *et al.* (2016), important formulas are thus given here. The relationship between the base load and yearly growth rate is given as:

$$Y = Ae^{Bx} \tag{9}$$

Taken the natural logarithm of both sides of (9) the following equation is obtained:

$$lnY = lnA + Bx. \tag{10}$$

$$\sum lnY = \sum lnA + B\sum X \tag{11}$$

$$\sum XlnY = n\ lnA \sum X + B \sum X^2 \tag{12}$$

Solving (11) and (12) simultaneously, the coefficients a and b are obtained thus:

$$lnA = a = \frac{\sum lny \sum x^2 - \sum xlny \sum x}{n(\sum x^2) - (\sum x)^2} \tag{13}$$

$$B = \frac{n\sum(xlny) - \sum x(\sum lny)}{n(\sum x^2) - (\sum x)^2} \tag{14}$$

2.3.4 *Performance Metrics:* The performance metrics used in this analysis are Mean Average Percentage Error (MAPE) and Root Mean Square Error (RMSE). These indices are expressed by (15) and (16) respectively.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Actual_{Load} - Forecasted_{Load}|}{Actual_{Load}} \times 100\% \tag{15}$$

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_t - y_t)^2}{n}} \tag{16}$$

Where, $\hat{y}_t$ is the forecasted load (MW) and y_t is the actual load (MW).

Least value of MAPE and RMSE gives optimal performance. To carry out load forecasting using least square and regression exponential techniques, Table 1 is formulated from the data collected.

Table 1. Monthly energy consumption (MW) for mathematical modelling for August – December, 2017

Months	Month Index (X)	Actual Load, Y (MW)	lnY	$XlnY$	X^2	XY
August	-2	107.86	4.6808	-9.3616	4	-215.72
September	-1	107.01	4.6729	-4.6729	1	-107.01
October	0	118.92	4.7784	0	0	0.000
November	1	118.67	4.7763	4.7763	1	118.67
December	2	127.74	4.8500	9.7000	4	255.48
$\sum Total$	**0**	**580.20**	**23.7584**	**0.4418**	**10**	**51.42**

3. Results and Discussion

The actual monthly energy consumption (MW) for the month of August-December, 2017 is shown in Table 2. The modelled equation obtained for Least Square technique after substituting for each term in (7) and (8) using the values presented in Table 1 is given by the equation:

$$Y = 116.04 + 5.142X \tag{17}$$

Substituting for the assigned value of X corresponding to each month in Table 1, that is August ($X = -2$), September ($X = -1$) etc., the forecasted load with this approach is as shown in Table 3.

A graphical comparison of the forecasted load obtained using least square approach with the actual monthly energy consumption alongside the error gap between the forecasted load and the actual load for the months of August to December, 2017 is as shown in Figure 2. It is observed that the forecasted load with this approach gave a result that is almost the same in value with the actual load consumed in the months under consideration, this reflects that the proposed approach is adequate to predict what load consumption will be in the state.

Table 2. Actual monthly energy consumption (MW)

Months (2017)	Actual Load (MW)
August	107.86
September	107.01
October	118.92
November	118.67
December	127.74

Table 3. Forecasted load with least square approach (MW)

Months (2017)	Forecasted Load (MW)	Error Gap (MW)
August	105.76	2.10
September	110.89	3.88
October	116.04	2.88
November	121.18	2.51
December	126.74	1.42

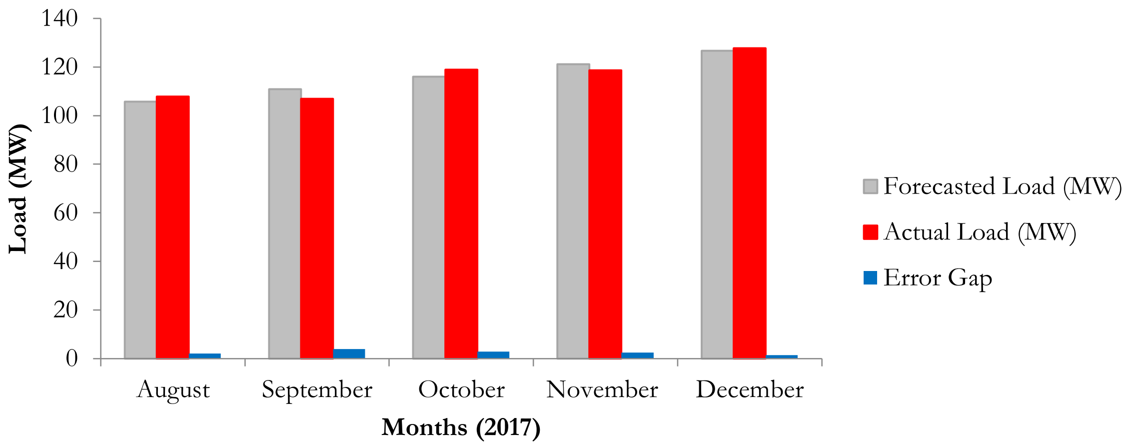

Figure 2. Comparison of Forecasted Load, Actual Load and Error Gap

The modelled equation for the regression exponential model after substituting for each term in (13) and (14), gives:

$$Y = 115.78 + 10.7X \tag{18}$$

Substituting for X, say August (X= -2), September (X= -1) etc., the forecasted load with this approach is as presented in Table 4. A graphical comparison of the forecasted load obtained using least square approach with the actual monthly energy consumption alongside the error gap between the forecasted load and the actual load for the months of August to December, 2017 is shown in Figure 3. An appreciable gap error was observed in the months of August, November and December while the forecasted load and the actual load in the month of September and October is fairly the same.

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Table 4. Forecasted load using regression exponential approach

Months (2017)	Forecasted Load (MW)	Error Gap (MW)
August	94.38	13.48
September	105.08	1.93
October	115.78	3.14
November	126.48	7.81
December	137.18	9.44

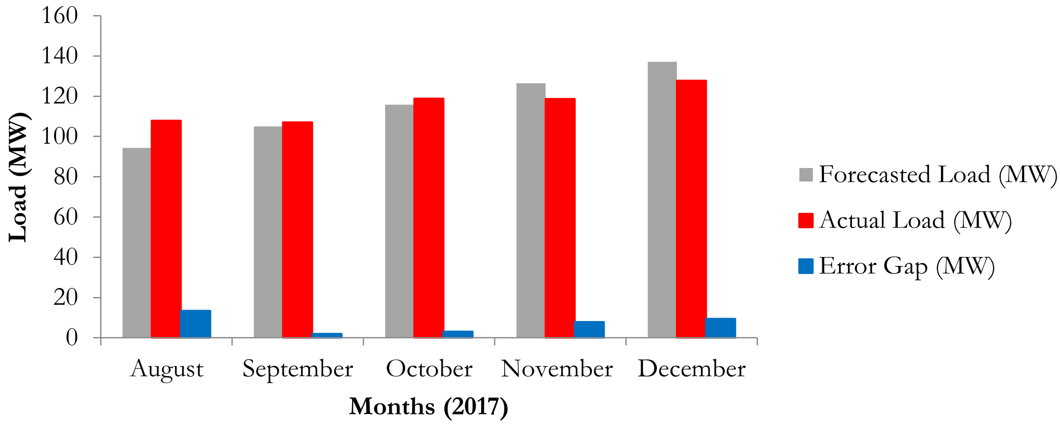

Figure 3. Comparison of forecasted load, actual load and error gap

The MAPE and RMSE computed for all the two approaches is as shown in Table 5, the approach with the least optimal values of MAPE and RMSE has the optimal solution. From the analysis, it is shown that least square approach (LSR) has the least values of MAPE and RMSE. The approach with the least value of MAPE and RMSE is best suited to make forecast. Linear regression approach is therefore employed for the forecast. The forecast for the months of July- December, 2018 is as shown in the Table 6.

Table 5. A comparison of MAPE and RMSE values for the LSA and REA

Techniques	MAPE (%)	RMSE
Least Square Model	1.8212	0.004472
Regression Exponential Model	6.1820	0.5769

Table 6. Load forecasted for the months of July-December, 2018 using LSA

Months (2018)	No of Days	*X*	Load Forecasted *Y* (MW)	Load forecasted (MWh)
July	31	8	157.18	116,941.92
August	31	9	162.32	120,766.08
September	30	10	167.46	120,571.20
October	30	11	172.60	124,272.00
November	30	12	177.74	127,972.80
December	31	13	182.89	136,070.16

A substantial increase in load is anticipated based on the model used to forecast the expected load consumption in the state for the months of July-December, 2018 as compared with the monthly load consumption for 2017. Figure 4 presents a comparison of forecasted load for months under consideration in 2018 and the actual load consumed in 2017. The estimated percentage monthly load growth based on the least square approach used is as shown in the Figure 5.

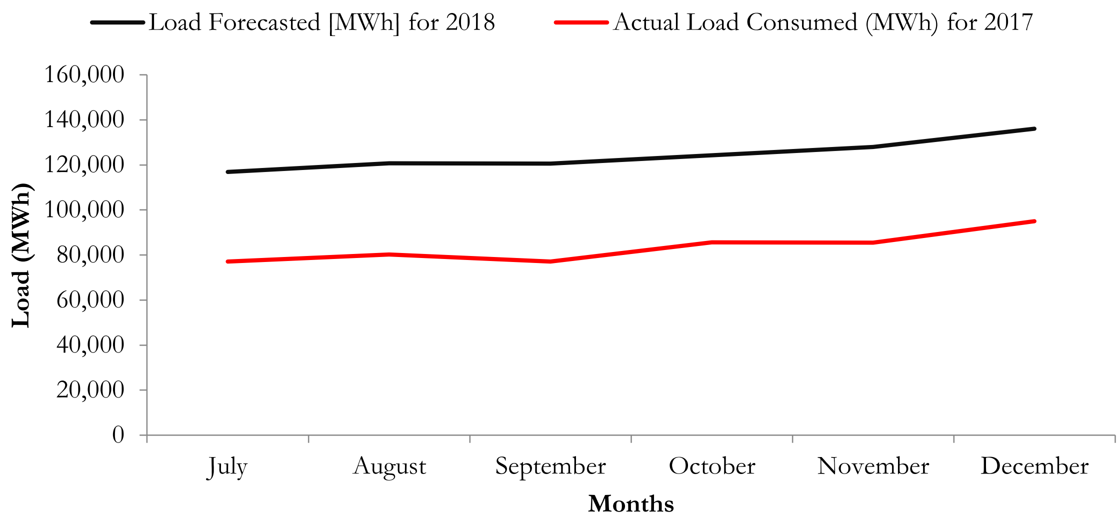

Figure 4. A comparison forecast load for 2018 and actual load consumed in 2017

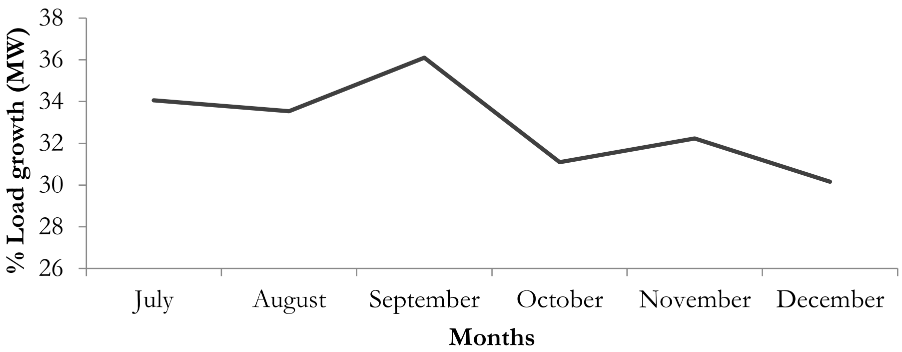

Figure 5. Percentage load growth (MW)

4. Conclusion

Performance evaluation of regression exponential and least square techniques on medium-term load forecasting: a case study of Ogun State, Nigeria was presented in this paper. Two different models were used to predict the expected load consumption for the entire state. Based on the results of the analysis, least square approach (LSA) gave the least value of MAPE and RMSE when compared with regression exponential approach. Having established the approach with least value of MAPE and RMSE, it was then employed to predict load consumption for months of July-December, 2018.

LSA used for the forecast revealed a significant load growth for each month, the percentage load growth was estimated to be 34.06%, 33.54%, 36.10%, 31.10%, 32.23% and 30.15% for the months of July-December respectively. The low percentage load growth in the month of December can be attributed to acute shortage in gas supply caused by pipeline vandalisation and theft of distribution/sub-station materials. The results of this research will in no small measure assist IBEDC, Ogun Region in making informed decision(s) concerning energy consumption pattern expected across the state for months under consideration.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix

Table A. The monthly energy consumption in Ogun region grid in the year 2017

Ibadan Electricity Distribution Company: Ogun Region Year Grid 2017 Energy							
Year 2017	**Ijeun BH**	**Olumo BH**	**Ijebu Ode BH**	**Sagagmu BH**	**Ota BH**	**Sango BH**	**Total**
January	5,624.13	7,356.30	7,073.00	11,241.70	17,392.57	12,039.00	60,726.70
February	6,302.97	7,549.87	6,742.00	14,666.30	17,949.95	10,966.80	64,177.89
March	5,736.42	6,852.44	6,673.00	13,851.30	16,386.00	8,619.90	58,119.06
April	7,189.02	7,027.60	8,241.00	11,520.60	18,241.73	11,943.80	64,163.75
May	7,985.02	8,965.36	7,787.00	14,078.80	19,348.91	13,254.80	71,419.89
June	9,749.24	9,364.32	7,824.00	12,837.10	18,768.55	14,459.10	73,002.31
July	9,649.95	9,631.27	8,805.00	18,169.60	17,691.58	13,204.10	77,151.50
August	8,189.82	9,183.75	8,839.00	22,389.60	18,963.74	12,684.90	80,250.81
September	8,267.31	8,975.48	11,167.00	16,137.70	19,613.15	12,888.60	77,049.24
October	7,677.64	8,967.76	10,319.00	25,527.40	19,132.61	13,998.90	85,623.31
November	8,037.68	9,046.83	11,778.00	19,692.85	20,833.14	16,057.60	85,446.10
December	9,745.67	11,155.85	9,081.00	25,918.28	22,621.59	16,518.00	95,040.39
Total							**892,170.95**

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